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# Precision landing using an adaptive fuzzy multi-sensor data fusion architecture

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ABSTRACT

The positional inaccuracies associated with the GPS/INS measurements make the terminal phase of the normal GPS/INS landing system imprecise. To solve this problem, an adaptive fuzzy data fusion algorithm is developed to obtain more accurate state estimates while the vehicle approaches the landing surface. This algorithm takes the translational displacements in x and y from the mounted Optical Flow (OF) sensor and fuses them with the INS attitude measurements and the altimeter measurements. This low cost adaptive algorithm can be used for vertical landings in areas where GPS outages might happen or in GPS denied areas. The adaptation is governed by imposing appropriate assumptions under which the filter measurement noise matrix $R$ is predicted. The $R$ matrix is continuously adjusted through a fuzzy inference system (FIS) based on the Kalman innovative sequence and the applied covariance-matching technique. This adaptive fuzzy Kalman fusion algorithm (AFKF) is used to estimate the vehicle's states while landing is being commanded. AFKF results are compared with these obtained using a classical Kalman estimation technique. The AFKF algorithm shows better states estimates than its conventional counterpart does. Compared to prior landing systems, the proposed low cost AFKF has achieved a precision landing with less than 10 cm maximum estimated position error. Real precision landing flights were conducted to demonstrate the validity of the proposed intelligent estimation method.



## 1. Introduction

A successful utilization of unmanned aerial Vertical Takeoff and Landing (VTOL) vehicles in missions that require a high degree of autonomy necessitates accurate and fast updated measurements from the onboard navigational sensors [1,2]. For example, the quality of the Global Positioning System (GPS) becomes low when the Unmanned Aerial Vehicle (UAV) is approaching the ground, and a landing with few meters' error might result. Therefore, the use of other more precise sensors is needed for the development of the sensor fusion design [3–6].

Vision sensors have been employed in designing autonomous landing systems in recent years due to their precision and high update rate measurements [7,8]. A vision-based helicopter-landing algorithm was proposed in [9]. The study achieved a precise landing with an average position error equal to 47 cm. However, their solution is computationally heavy and ill-suited for vehicles that have smaller payloads. In [10], a pattern of InfraRed (IR) LEDs organized in a T-shape and a Wii camera was utilized to perform an indoor auto takeoff, hovering and landing. The algorithm performs well at 60 cm height; however, at higher altitudes, the positional error will be large and inaccurate TOL might occur. In [11], a vision off-the-shelf hardware was used to provide real time estimates of the UAV orientation and the position relative to the landing position. Similarly, [12] studies the 6 Degree of Freedom (DOF) pose estimation of a Miniature Air Vehicle (MAV) using on-board monocular vision solutions.

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OF sensors are considered robust low cost navigational sensors for UAVs applications [13]. OF sensors are used to avoid collision, measure the altitude and for position stabilization during the landing stage. Furthermore, OF sensors are used for height estimation and terrain navigation [14]. In [15], the OF measurements were used to control the vertical landing on a non-stationary platform. Whereas, In [16], an OF sensor was utilized for the position estimation of a quadrotor, and an auto-landing with 30 cm position error was performed. In [17], PX4FLOW optical sensor was used to perform hovering in an outdoor flight trajectory for Cheetah quadrotor. The optical flow components measured by the PX4FLOW sensor are compensated for the 3D rotations and transformed to the metric scale.

Precise state estimation is needed for the UAV to perform successful autonomous flight. However, obtaining accurate states estimate is challenging due to the sensor drifts, noise on the onboard Commercial off-the-shelf (COTS) sensors and measurement bias [18]. Low cost COTS sensors with such expected errors are usually utilized in UAVs because of their lightweight, low power consumption and compact size. By fusing the measurements of different precise sensors, the chance of obtaining accurate estimates would be definitely higher. For example, in [19], the readings of the kinematic OF model are fused with the measurements of the GPS/INS to estimate the 3D velocity states and position of an object. In [20,21,18], a high-accuracy helicopter's attitude and flapping states estimation was addressed using the Kalman filter. The unmeasured flapping angles of the Maxi Joker 3 helicopter were estimated with maximum error not exceeding 0.3°.

The accuracy of the estimation algorithm in the Kalman filter is linked with the accuracy of the a priori information of the process and measurement noise statistics which are represented by the $R$ and $Q$ matrices [22,23]. Practically, inaccurate priori information will degrade the performance of the estimator, and a divergence of the filter might result. Therefore, the adaptive Kalman filter has been devised to tackle the problem of having imperfect a priori information [24–26]. The Kalman filter can be adapted using different procedures, i.e., Innovative-based Adaptive Estimation (IAE) and Multiple Model Adaptive Estimation (MMAE) [22]. The IAE technique depends on the enhancement of the filter performance via the adaptation of the matrices $R$ and $Q$ which are based on the filter innovation sequence. In [23,27,28], the IAE adaptation approach proves its capability of working with unknown measurement noise characteristics in the Kalman filter. Moreover, applying the fuzzy logic rules to adjust the statistical matrices has been studied in a number of published research papers. The fuzzy-adapted Kalman filter shows better performance in rejecting the measurement noise and estimating the navigational states accurately [29–31].

In this paper, the problem of precision terminal landing phase has been tackled using intelligent adaptive low cost multi-sensor data fusion architecture. This architecture proposes a novel multi-sensor data fusion between the experimentally obtained OF sensors' model, altimeter and INS solution for vertical precision landing applications. Compared to prior landing systems, the proposed integrated solution has succeeded in performing an autonomous precision landing in GPS denied environments with less than *5 cm* estimated altitude error. Moreover, the proposed intelligent estimation technique has shown high degree of robustness in the presence of external disturbances compared to the normal estimation techniques.

The following sections of the paper are organized as follows. Section 2 describes the quadrotor model used in this study and the optical flow modeling design. Section 3 represents the design of the proposed sensor fusion algorithm architecture. Simulation results are presented in Section 4 while Section 5 demonstrates the experimental validation. Finally, Section 6 concludes the paper.

## 2. Quadrotor model

Quadrotor has been increasingly studied as a preferred UAV platform for various applications. It is sustained in the air by the lift of four actuators, and it has six degrees of freedom. A typical quadrotor incorporated in multi-rotor cross platform is composed of four symmetrical arms. Each of its four actuators is connected to a propeller with fixed-pitch blade, and the axes of rotation of the four propellers are fixed and parallel to each other (see Fig. 1). The system state variables can be controlled using different movements directly related to the propellers velocities, which allow the quadrotor to reach a desired altitude and attitude [32].

### 2.1. Reference frame

This section describes the various reference frames and rotation matrix that are used to describe the position and the orientation of the quadrotor. In addition, it shows the nonlinear dynamic equation of the quadrotor. The linear position ($\Gamma$) is determined using the vector between the origins of the B-frame and E-frame. The attitude of the vehicle is represented by the Euler angles$\left(\boldsymbol{\Theta} = \begin{bmatrix} \phi & \theta & \psi \end{bmatrix}^T\right)$. These angles are defined by the orientation of B-frame with respect to the E-frame.

To map the orientation of a vector from B-frame to E-frame, a rotation matrix is needed [33]. This rotation matrix is given by:

$$R = \begin{bmatrix} c_\theta c_\psi & -c_\phi s_\psi + c_\psi s_\phi s_\theta & s_\phi s_\psi + c_\phi c_\psi s_\theta \\ c_\theta s_\psi & c_\phi c_\psi + s_\phi s_\theta s_\psi & -c_\psi s_\phi + c_\phi s_\theta s_\psi \\ -s_\theta & c_\phi s_\theta & c_\phi c_\theta \end{bmatrix} \tag{1}$$

Where $c_x = \cos(x)$ and $s_x = \sin(x)$.

Along with the rotation matrix, a transfer matrix is needed to map the relation between the angular velocity ($\boldsymbol{\omega}$)in the B-frame and Euler angles rates $\left(\dot{\Theta}\right)$ in the E-frame. This matrix is defined as follows [33]:

$$\dot{\boldsymbol{\Theta}} = \boldsymbol{T}\boldsymbol{\omega} \tag{2}$$

$$\boldsymbol{T} = \begin{bmatrix} 1 & s_\phi t_\theta & c_\phi t_\theta \\ 0 & c_\phi & -s_\phi \\ 0 & s_\phi / c_\theta & c_\phi / c_\theta \end{bmatrix} \tag{3}$$

Where $t_x = tan(x)$.

### 2.2. Dynamical model

Several dynamical models can be used to characterize the quadrotor dynamics. These models differ due to the various assumptions and simplifications that can be made to reduce the model complexities. As an illustration, having the vehicle aerodynamics into consideration would complicate the dynamical model to a high extent. Another well-used simplification is to consider the small angle assumption for miniature quadrotors. Reference [34] reviews dynamic models and controls of the quadrotor. A typ-